# Channel Equalization using Fuzzy-ARTMAP

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## ABSTRACT

In this paper, fuzzy-ARTMAP equalizer is developed mainly for overcoming the obstacles, such as complexity and long training, in implementing the previously developed neural-basis equalizers. The proposed fuzzy-ARTMAP equalizer is fast and easy to train and includes capabilities not found in other neural network approaches; a small number of parameters, no requirements for the choice of initial weights, no risk of getting trapped in local minima, and capability of adding new data without retraining previously trained data. In simulation studies, binary signals were generated at random from linear channel with Gaussian noise. The performance of the proposed equalizer is compared with other neural net basis equalizers, such as MLP and RBF equalizers. The fuzzy ARTMAP equalizer combines relatively simple structure and fast processing speed; it gives accurate results for nonlinear problems that cannot be solved with a linear equalizer.

# 퍼지-ARTMAP에 의한 채널 등화

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## 요 약

본 논문에서는 이전에 개발된 신경회로망 채널 등화기에서 볼 수 있었던 구조의 복잡성 및 많은 학습시간의 소요 등과 같은 단점을 극복하고자 퍼지-ARTMAP 신경망을 이용하여 채널 등화기를 구성하였다. 제안된 퍼지-ARTMAP 채널 등화기는 다른 형태의 신경망을 이용한 등화기에서는 찾아 볼 수 없는 빠르고 쉬운 학습 능력을 갖고 있다. 즉, 등화기 구성에 필요한 파라미터의 수가 적으며 지역적 최소값에 빠질 우려 없이 각 계층간의 초기 연결강도를 지정할 수 있을 뿐만 아니라 기존의 학습된 데이터를 재학습 시킬 필요 없이 새로운 데이터를 단순히 추가 학습시킬 수 있는 장점 등을 가지고 있다. 본 연구의 시뮬레이션 과정에서는 선형채널에서 발생된 가우시안 잡음을 동반한 이진 신호를 대상으로 퍼지-ARTMAP 채널 등화기의 성능을 LMS 기반의 선형등화기 및 MLP와 RBF 신경망 등화기와 비교하였으며 퍼지-ARTMAP 등화기가 상대적으로 간단한 구조와 빠른 처리속도를 가짐은 물론 선형등화기로 해결하지 못했던 비선형 문제들도 해결할 수 있음을 보였다.

## 1. Introduction

In digital communication systems, data symbols are transmitted at regular intervals, but time dispersion caused by the non ideal channel frequency response characteristics, or by multipath transmission, may create intersymbol interference(ISI). To deal with ISI, many researchers have been concerned with applying neural networks, such as multilayer perceptron(MLP) and radial basis functions(RBF), to equalizers [1-6]. The basis idea of applying neural network to equalization comes from the fact that channel equalizer problems can be regarded as patterns classification(detection). Previous studies have shown that neural networks based equalizers are superior to a linear equalizer in handling the situation where the channel suffers from high levels of additive noise and highly

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nonlinear distortion. However, each of these networks internally has significant shortcomings. MLP equalizers typically require long training and are sensitive to the initial choice of network parameters(specially initial weights). Also, RBF equalizers is simple and fast to train, but usually require a large number of centers, which increases the complexity of computation.

In contrast, the adaptive resonance theory (ART) neural network provides the desirable characteristics of fast training and user control of network complexity[7-9]. Predictive ART networks, such as the fuzzy adaptive resonance theory mapping(ARTMAP) used in this paper, increase the network architecture(number of clusters) to the minimum level necessary for perfect performance on the training data[10-12].By selecting the desired level for the vigilance parameter, the user has control over the performance of the network on data that were not used in training; the network will recognize input that is not sufficiently similar to training data as novel.

This paper proposes a fuzzy-ARTMAP basis equalizer, that is much simple and fast to train, to deal with ISI. The proposed fuzzy-ARTMAP equalizers provides attractive characteristics that are not found in previously developed neural-basis equalizers; a small number of parameters, fast and easy training, no requirement for the choice of initial weights, and capability of adding new data without retraining previous patterns. Section 2 presents a brief summary of the fuzzy ARTMAP network and learning mechanism. Section 3 gives the structure and learning procedure for the fuzzy ARTMAP equalizer. Experimental results are provided in Section 4, and Section 5 gives the conclusions.

## 2. Fuzzy ARTMAP Neural Network

ARTMAP[10] is a supervised neural network that learns recognition categories in response to input vectors. Fuzzy ARTMAP[11], a generalization of ARTMAP, accepts input vectors with components in the range [0,1]. ARTMAP networks (either the original or fuzzy form) consist of two ART modules, connected by a mapfield. The ART modules serve to cluster the input and target vectors, subject to the user specified vigilance; the mapfield provides the predictive link between the input and output modules. A schematic diagram of a fuzzy ARTMAP network is shown in Fig. 1.

During training, the network can adjust (increase) the user specified vigilance, if necessary, so that the training input-output pairs are learned perfectly. After training, an input pattern that is sufficiently similar to a training input will produce the corresponding training output as response. Input which is not sufficiently similar will be recognized as novel, and no prediction of a response is made. The vigilance value specified by the user determines the required degree of similarity. Details of the fuzzy ARTMAP network are given in[11].

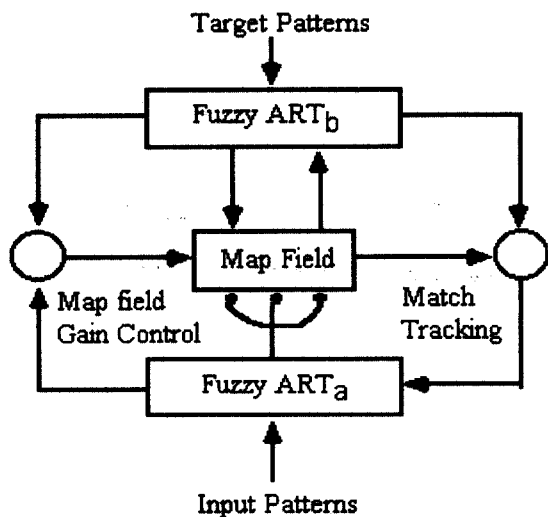



Fig. 1. Fuzzy ARTMAP structure diagram

## 3. Implementation of Fuzzy ARTMAP Equalizer

In order to train a neural network to serve as a channel equalizer, it is necessary to generate

appropriate training data. In this study, the network is trained to reconstruct the original signal (1 or -1) based on the signal received after transmission over a dispersive channel, as shown in Fig. 2. Therefore, input patterns for the network consist of received signals and the corresponding target is the original transmitted signal. The channel is characterized by its transfer function, which in general has the form

$$H(Z) = \sum_{n=0}^{p} h_n Z^{-n} , \tag{1}$$

where $p$ is the channel order. If $q$ denotes the equalizer order(number of tap delay elements in the equalizer), then there are $M=2^{p+q+1}$ different sequences

$$\mathbf{A}_k = [a_k, a_{k-1}, \ldots, a_{k-p-q}]^T \tag{2}$$

that may be received(where each component is either 1 or -1). For a specific channel order and equalizer order, the required number of training patterns is $M$.

If pure training patterns were available, they could be used directly, but if ARTMAP is to be trained with noisy signals, preprocessing is necessary to prevent the network from learning the noise. In this study, the action of noisy transmission path is simulated by adding Gaussian noise

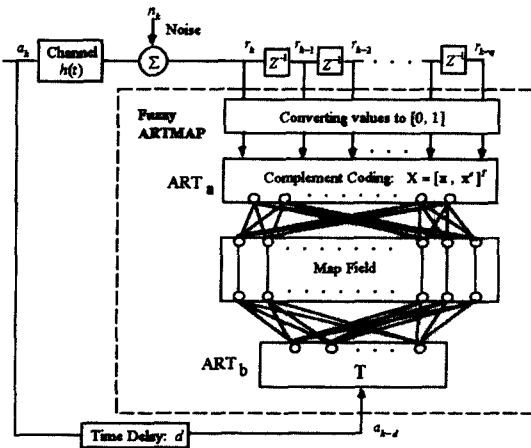



Fig. 2. The structure of Fuzzy ARTMAP equalizer system

to the received signal after each possible transmission sequence is passed through the transfer function. The training patterns are generated by applying the supervised K-means clustering algorithm[2] to remove the Gaussian noise:

Algorithm:{Supervised K-means clustering}

$if(\mathbf{A}_k = \mathbf{A}_i)\{$

$counter_i = counter_i + 1;$

$\mathbf{D}_i = \dfrac{(counter_i - 1)\cdot \mathbf{D}_i + \mathbf{R}_k}{counter_i};$

$\}$

where

$$\left.\begin{aligned} \mathbf{D}_i &= [d_{i0}, d_{i1}, \ldots, d_{iq}]^T, \\ \mathbf{R}_k &= [r_k, r_{k-1}, \ldots, r_{k-q}]^T, \\ i &= 1,2,\ldots, M, \end{aligned}\right\} \tag{3}$$

and $A_i$, $R_k$, and $D_i$ are the combination of $A_k$, the received signal vectors, and a training pattern, respectively. As shown in eq.(3), the number of components in the $R_k$ is $q$+1. To facilitate the graphical representation of the network input vectors, the example given below is limited to equalizer order $q$+1, so that the input vectors have two components.

The training patterns which come from the transfer function (either directly or after the noise removal) have components that are not in the correct range for fuzzy ARTMAP. The actual range depends on the transfer function; however, the binary sigmoid

$$\frac{1}{1+e^{-\sigma x}} \tag{4}$$

converts the interval [-n,n] to [0,1], and thus is suitable for making the required conversion for any transfer function. The final input vectors after converting and complement coding procedures are

$$\mathbf{X}_i = [\mathbf{x}_i,\ \mathbf{x}_i^c]^T,\ i = 1,2,\ldots, M \tag{5}$$

where

$$\mathbf{x}_i = [x_{i0}, x_{i1}, \ldots, x_{iq}], \tag{6}$$

$$\mathbf{x}_i^c = [1-x_{i0}, 1-x_{i1}, \ldots, 1-x_{iq}], \tag{7}$$

$$x = \frac{1}{1+\exp(-\alpha \cdot d_{ij})}, j = 0, 1, \ldots, q \tag{8}$$

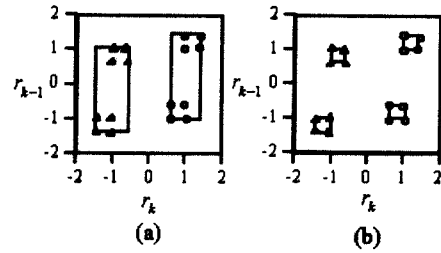
The target value for each generated training pattern is the correct value for $a_{k-d}$ for the desired delay, $d$. The appropriate value of is determined by the dominant term in the transfer function. A target value of 1 is represented by the vector (1,0); the target value of -1 is given by the vector (0,1).

To generate training patterns for a given channel input matrix and noisy channel output vector, it is necessary to estimate the channel order. This is done using regression analysis [3].

## 4. Simulation Results

The fuzzy ARTMAP equalizer was applied to several linear channels with different transfer functions. Among the favorable characteristics of this network is the fact that there are relatively few network parameters to be determined. The steepness of the sigmoid function( $\alpha$ in eq. (4)) used to convert the input patterns into the required interval (0,1) and the vigilance parameter for the networks must be set by the user. The network is not particularly sensitive to the values of either of these parameters. Sigmoid steepness parameter values in the range(0.7,1.0) were used. The value of the vigilance influences the number of clusters formed(as is well known), but ARTMAP networks increase the vigilance, if required, to ensure that the training data are learned perfectly. The value of the vigilance has a more pronounced effect on the performance of the network after training, since the network will reject as unknown any input that is not sufficiently similar(based on the vigilance value) to the training patterns.

In Fig. 3, there are 16 patterns that are estimated from the noisy received signals by using the supervised K-means clustering.

As shown in Fig. 3, high vigilance results inmore clusters, and the error rate performance with

$H(Z)=0.2+1.0Z^{-1}+0.2Z^{-2}$, $q=1$, $d=1$

circles : patterns with $a_{k-1}=1$,
triangles : patterns with $a_{k-1}=-1$,
(a) vigilance parameter = 0.7, 2 clusters
(b) vigilance parameter = 0.85, 4 clusters

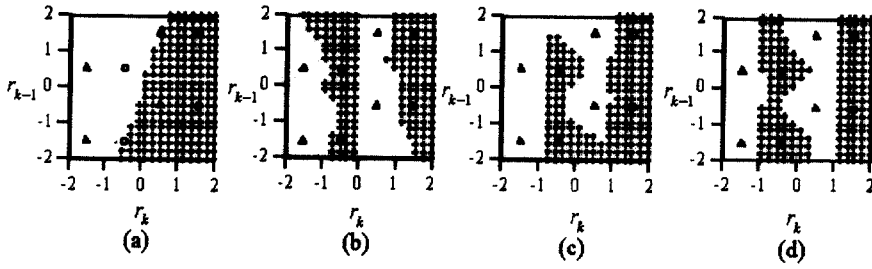
Fig. 3. Comparison of the number of clusters

high vigilance was better than with low vigilance. The vigilance value also affects the region which each cluster will accept when the net is applied (after training). The cluster will accept all points that fall within the boundaries shown, and also points somewhat outside the dotted rectangle region.

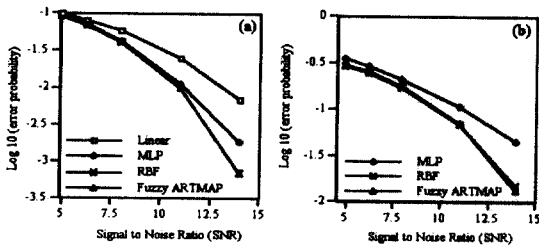
A comparison of the performance of the fuzzy ARTMAP equalizer to that of a linear equalizer, and two other neural network equalizers is illustrated in Fig. 4 for the transfer function

$$H(Z) = 0.5 + 1.0Z^{-1} \tag{9}$$

with $q$=1 and $d$=0. As shown in Fig. 4(a), the nonlinear decision boundaries cannot be achieved by the linear equalizer. The response regions for the radial basis function network and the fuzzy ART MAP equalizer are similar. In MLP equalizer case, the number of units used in input, hidden, and output layers were two, eight, and one, respectively. The RBF equalizer uses eight centers which are estimated from supervised K-means clustering. For the Fuzzy ARTMAP equalizer, the vigilance, and sigmoid steepness parameters were 0.95, and 0.6 respectively.

Fig. 5 shows the error rate comparison of linear and three kinds of neural network equalizers over two different channel delays that were introduced

$H(Z)=0.5+1.0Z^{-1}$, $q=1$, $d=0$

circles: patterns with $a_k=1$,
triangles : patterns with $a_k=-1$,
(a) linear equalizer, (b) MLP equalizer, (c) RBF equalizer, (d) Fuzzy ARTMAP equalizer

Fig. 4. Comparison of nonlinear decision boundary

$H(Z)=0.5+1.0Z^{-1}$, $q=1$

(a) $d=1$(desired symbol $a_{k-1}$),
(b) $d=0$(desired symbol $a_k$)

Fig. 5. Error rate comparison

in training. The performance of the fuzzy ART MAP equalizer is superior to that of both linear and MLP equalizers, while producing favorable results as in RBF equalizer. Although the performance of the RBF equalizer is almost the same as that of fuzzy ARTMAP equalizer, fuzzy-ARTMAP e-qualizer is more attractive candidate than RBF equalizer, considering the cost and efforts required in neural network implementation. Here, MLP and RBF equalizers uses eight numbers of hidden units, or centers, while fuzzy ARTMAP equalizer re-quires four clusters for linear decision boundary case, and the training period of the fuzzy ARTMAP equalizer was approximately one third times that of other two neural network equalizers.

## 5. Conclusions

In this paper, a new fuzzy-ARTMAP equalizer system is developed mainly for solving the pro-blems of long time of training and complexity, which are often encountered in previously devel-oped neural-basis equalizers such as MLP and RBF equalizers. The fuzzy-ARTMAP equalizer is fast and easy to train and includes capabilities not found in other neural network approaches; a small number of parameters, no requirements for the choice of initial weights, no risk of getting trapped in local minima, and capability of adding new data without retraining previously trained data. Throu-ghout the simulation studies, it was found that an fuzzy ARTMAP equalizer performed favorably better than the MLP equalizer, while requiring rel-atively smaller computation steps in training. The main advantage of the proposed fuzzy ARTMAP is fast training due to the structural simplicity of fuzzy ARTMAP. The superiority of fuzzy ART MAP to other neural networks makes the imple-mentations of fuzzy-ARTMAP equalizer feasible. As a further research, we are under processing of applying the fuzzy-ARTMAP to satellite nonlinear channel.

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